CDS Exposure and Credit Spreads

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Abstract: In this paper we provide evidence that CDS influence the ex-ante price of the underlying bond because the frictions they introduce in renegotiation affect ex-post default and renegotiation decisions. Bondholders who hedge their default risk with CDS (empty creditors) favor default over renegotiation because CDS insurance makes them whole in default, while renegotiation involves granting concessions. Their resistance to renegotiation increases the risk of inefficient liquidity default but it also decreases the risk of strategic default. Proxying for this resistance by the net notional amount of CDS outstanding (CDS exposure), we find that credit spreads are positively related to CDS exposure. This finding implies that CDS impose costs associated with inefficient liquidation in liquidity default that outweigh the benefits associated with deterring strategic default. Furthermore, we find that the costs associated with inefficient liquidation increase in liquidation costs (renegotiation surplus) while the benefits associated with deterring strategic default increase in borrower bargaining power (share of the renegotiation surplus). Our evidence thus indicates that CDS are not redundant securities and that they increase the cost of debt.

1 Introduction

Credit Default Swaps (CDS) are derivative securities that offer a buyer recovery of credit loss if the underlying bond were to default, in exchange for a premium. Over the last decade or so, CDS have developed as important complements to modern day corporate bond markets by expanding the opportunities available to market participants to hedge default risk. In a complete contracting world where renegotiation is either impossible or costless, the ability to hedge default risk has no valuation consequences; CDS represent risk-sharing arrangements that have no effect on the underlying bond's default risk or its price. In an incomplete contracting world where renegotiation is possible, CDS can influence the ex-ante price of the underlying bond because the frictions they introduce in renegotiation affect ex-post default and renegotiation decisions. Bondholders who hedge in the CDS markets (empty creditors) favor default over renegotiation because CDS insurance makes them whole in default while renegotiation entails granting concessions. Their resistance to renegotiation increases the risk of inefficient liquidity default but it also decreases the risk of strategic default. Proxying for this resistance by the net notional amount of CDS outstanding (CDS exposure), we find that ex-ante credit spreads on non-distressed bonds increase with CDS exposure. This finding implies that CDS impose costs associated with inefficient liquidation in liquidity default that outweigh the benefits associated with deterring strategic default. Furthermore, we find that the costs associated with inefficient liquidation increase in liquidation costs (renegotiation surplus) while the benefits associated with deterring strategic default increase in borrower bargaining power (share of the renegotiation surplus). Our evidence thus indicates that CDS are not redundant securities and that they increase the cost of debt.

The theoretical literature on incomplete contracting (Hart and Moore, 1994, 1998) emphasizes that default can occur either because of liquidity reasons when the firm's cash flows are insufficient to cover the bond's contractual obligations (liquidity default), or for strategic reasons when the firm chooses not to fulfill its contractual obligations despite having the resources to do so (strategic default.) In liquidity default, ex-post renegotiation may be mutually beneficial to both the firm and its bondholders in preserving going concern value and preventing inefficient liquidation. When liquidation value is lower than going concern value, bondholders may be willing forgive some debt to enable the firm to survive and maximize their recoveries. However, knowledge that bondholders would be willing to do so also provides incentives for debtors to act strategically and threaten default to extract such concessions.

CDS affect these ex-post default and renegotiation decisions because of the friction they introduce in renegotiation. When bondholders hedge using CDS, they functionally decouple their cash flows from their control rights thereby becoming, what Hu and Black (2008a, b) term, "empty creditors." Empty creditors' incentives are to resist renegotiating with a distressed firm because renegotiation requires granting concessions to avoid default when default would allow them to recover par (Lubben, 2007; Hu and Black, 2008a,b). Empirical evidence supports the presence of such resistance (Narayanan and Uzmanoglu, 2014; Danis, 2013). In a model where the limited ability of debtors to commit to fulfilling their payment obligations (because realized cash flows are not verifiable) leads to the possibility that debtors may default not just for liquidity reasons, but for strategic reasons as well, Bolton and Oehmke (2011) show that empty creditor resistance generates two opposing effects. On the one hand, the unwillingness of empty creditors to renegotiate serves to commit the debtor against strategic default thereby generating efficiencies (raising debt capacity). On the other hand, the same unwillingness of empty creditors to renegotiate also generates inefficiencies because it makes default more likely when renegotiation would have been value preserving in liquidity default situations. In their model, the socially optimal level of CDS insurance trades off the ex-ante commitment benefits against the ex-post costs of inefficient renegotiation, but empty creditors do not fully internalize the cost of foregone renegotiation surplus. As a result, even when CDS spreads incorporate effects associated with empty creditors, empty creditors will over-insure and resist renegotiations, and in equilibrium, default (bankruptcy) will be inefficiently high compared to the social optimum.

Structural models of bond pricing that allow for renegotiation incorporate the effects of ex-post default and renegotiation on bond prices either by exogenously specifying the bargaining that occurs in renegotiation which affects recovery rates (Longstaff and Schwarz, 2005), or by endogenizing the firm's default decision which affects when or whether the firm chooses to default (Anderson and Sundaresan, 1996; Mella-Barral and Perraudin, 1997). Fan and Sundaresan's (2000) model endogenizes the bargaining that occurs in renegotiation to illustrate the crucial role played by the distribution of bargaining power between the firm and its bondholders in both ex-post default and renegotiation decisions. In liquidity default, renegotiation can help avoid inefficient liquidation. However, if all bargaining power rests with the firm (equity holders), the possibility of renegotiation increases the risk of strategic default thereby decreasing ex-ante bond prices (increasing ex-ante bond spreads). Conversely, if all bargaining power rests with the bondholders, the firm's incentive to default strategically decreases because of the greater share of the surplus bondholders stand to gain in renegotiation thereby increasing ex-ante bond prices. The net effect of ex-ante strategic default and ex-post bargaining in default on bond spreads is thus a function of the balance of bargaining power between the firm and its bondholders. Interpreting Bolton and Oehmke's arguments in the context of Fan and Sundaresan's model, CDS strengthen the hand of bondholders, which has two opposing effects on bond prices. On the one hand it could increase bond prices because it reduces the risk of strategic default. On the other hand, it could increase bond prices because it increases the risk of inefficient liquidity default. Thus the net of effect of CDS on ex-ante bond spreads is an empirical question.

First generation structural models of bond pricing (in the Black-Scholes-Merton framework) assume a complete contracting environment where renegotiation is either impossible or costless. As a result the only risk factors relevant to bond pricing are volatility and leverage. To examine bond pricing when renegotiation is a possibility, Davydenko and Strebuleav (2007) introduce variables that affect the possibility of renegotiation to show that ex-ante credit spreads reflect renegotiation frictions (for e.g. dispersed bondholders, collateralization). Furthermore, they show that the effect of renegotiation frictions on ex-ante credit spreads depends on liquidation costs (which measure the surplus that can be preserved through renegotiation) and the distribution of bargaining power (which measures the division of the surplus). We follow a similar empirical approach and examine whether ex-ante credit spreads reflect the frictions CDS introduce in renegotiation.

We proxy for the frictions CDS introduce in renegotiation by the net notional amount of CDS outstanding as a percentage of debt (CDS exposure). We find that ex-ante credit spreads are positively related to CDS exposure. This finding implies that the renegotiation frictions CDS introduce impose costs associated with inefficient liquidation that outweigh the benefits associated with deterring ex-ante strategic default. Although this net effect is robust and statistically significant, its quantitative contribution to the average and cross-sectional variation in spreads is below the costs for a round-trip transaction in the corporate bond markets. A one standard deviation (25%) increase in mean CDS exposure (20%) increases credit spreads by 12 bps, while the round-trip transaction costs reported by Schulz (2001) are 27 bps. However, if bondholders were to over-insure (CDS exposure greater than 100%) as Bolton and Oehmke (2011) suggest, our findings indicate that the increase in credit spreads may be substantial, and the economic effects meaningful. Our results remain significant after we control for the potential endogenity of CDS exposure.

We also examine how the effect of CDS exposure on ex-ante credit spreads varies with liquidation costs. Liquidation costs magnify the effect of the frictions CDS introduce in renegotiation on both ex-post default and renegotiation decisions. When liquidation costs are high, the greater losses in liquidity default imply that bondholders stand to gain more from renegotiation. Because CDS impede renegotiation, the risk of inefficient liquidity default increases, implying that the positive effect of CDS on ex-ante credit spreads should increase with liquidation costs. However, when liquidation costs increase, bondholders also stand to lose more in default which weakens their bargaining position and increases the risk that the firm may try to extract concessions by threating default. Because CDS impede renegotiations, the risk of strategic default decreases, implying that the negative effect of CDS on ex-ante credit spreads should also increase with liquidation costs. We find that positive effect of CDS exposure on ex-ante credit spreads in increasing in liquidation costs. This finding implies that the frictions CDS introduce in renegotiation impose costs on bondholders associated with inefficient liquidity default that are more pronounced when liquidation costs are high.

Finally, we examine how the effect of CDS on ex-ante credit spreads varies with the bargaining power the firm has over its bondholders. When the firm has greater bargaining power over its bondholders, the risk of strategic default increases. Furthermore, the greater bargaining power of the firm also reduces the bondholders' share in the renegotiation surplus. The frictions CDS introduce in renegotiation benefit bondholders both by reducing the risk of strategic default and by reducing the ability of the firm to extract concessions in renegotiations. Thus the negative effect of CDS on ex-ante credit spreads should increase with the bargaining power of the firm over its bondholders. We find that the negative effect of CDS exposure on ex-ante credit spreads increases as the firm's bargaining power increases. This finding implies that the frictions CDS introduce in renegotiation provide benefits to bondholders that are more pronounced when the firm's bargaining power high.

Our findings contribute to the literature in three ways. First, they show that CDS are not redundant securities, and that they increase a firm's cost of debt. Ashcraft and Santos (2009) examine at-issue yields for bonds and loans and find that the introduction of CDS has a material impact on yields only on riskier and informationally opaque firms. Our evidence complements theirs by showing that the influence of CDS on the cost of debt depends on the frictions they introduce and that secondary market yields on bonds reflect higher costs for firms with higher CDS exposure. Second, our findings add to the growing literature that examines the influence of the frictions CDS introduce in renegotiation on firms. Mengle (2009) and Bedendo, Catchcart, and Jahel (2012) study whether this friction leads to a disproportionate incidence of bankruptcy relative to out-of-court restructurings (distressed exchanges). They find that it does not. Danis (2013) examines distressed exchanges to provide evidence from tendering rates that such frictions do exist, while Narayanan and Uzmanoglu (2014) provide evidence of how firms structure distressed exchanges to overcome this resistance. Peristiani and Sarino (2011) and Subrahmanyam, Tang, and Wang (2014) provide evidence that the default risk of the firm increases upon the inception of CDS trading supporting that contention that CDS introduce frictions in renegotiation. Sarreto and Tookes (2013) show that the frictions CDS introduce in renegotiation allow the firm to raise its debt capacity by reducing the risk of strategic default. Our paper adds to this literature by examining the frictions CDS introduce in renegotiation on ex-ante credit spreads. Third our findings contribute to the literature that establishes the relevance of strategic actions for spreads. Davydenko and Strebuleav (2007) examine the relationship between spreads and firm-specific variables that influence the strategic behavior of debtors and creditor and provide evidence that spreads reflect the possibility of strategic behavior. Our study follows theirs providing evidence that the influence of CDS on strategic behavior concerning ex-post default and renegotiation decisions are priced ex-ante in spreads.

The rest of the paper is organized as follows. Section 2 describes the institutional aspects of CDS, surveys the related literature, and develops testable hypotheses. Section 3 provides details on the data, the sample selection process, and the empirical design. Section 4 presents the results and the robustness tests. Section 5 concludes with a summary of our findings.

2 CDS, literature review, and hypothesis development

2.1 CDS contracts

A single name CDS contract promises the protection buyer full recovery on the reference obligation if a credit event occurs. In return for protection, the CDS buyer makes fixed payments to the protection seller generally in quarterly installments. The annual fee for the protection is called the CDS spread. The protection seller (counterparty) receives the spread and pays out the losses of insured creditors only if a credit event occurs. CDS can be settled physically or in cash. In a physical settlement, the protection buyers deliver one of the qualified obligations and receive the par value of the bond while in a cash settlement, the protection buyer receives the difference between the par and the market value of the underlying obligation.[1] Given that the secondary market for distressed bonds is relatively illiquid, higher demand for the underlying bonds following a credit event may distort bond prices in a physical delivery. Hence, cash settlement has become the preferred method of delivery in the recent years.

CDS contracts adhere to protocols developed by the International Swaps and Derivatives Association (ISDA). When a credit event occurs, either the protection buyer or seller notifies the ISDA Determination Committee for evaluating the event. The 2003 ISDA Credit Derivatives Definitions define six broad credit events: bankruptcy, failure to pay, obligation acceleration, obligation default, repudiation/moratorium, and restructuring. The restructuring event, which involves exchanging and altering the terms of multiple securities, was subject to considerable ambiguity as a credit event, because it represents a voluntary renegotiation between the firm and its creditors. ISDA addressed this ambiguity in the spring of 2009 with a new protocol that eliminated restructuring as a credit event. According to Altman and Karlin (2009), none of the distressed exchanges conducted by firms prior to 2009 were deemed by ISDA to be a credit event.

2.2 Literature review on CDS

Legal scholars Henry Hu and Bernard Black were the first to identify the possible conflict between hedged creditors and the debtor. In a series of papers (Hu and Black, 2006a, 2006b, 2007, 2008a, 2008b) the authors propose that CDS contracts unbundle the ownership and cash flow rights, and this separation alters hedged creditor's incentives in debt contracting. Hedging with CDS contracts lowers creditor's economic exposure to the firm while still maintaining the

[1] Because bonds in the same seniority class may have different prices, in a physical settlement the CDS buyer has the option to deliver the cheapest bond in the class to the seller. In a cash settlement, the cheapest-to-deliver equivalent price is used to determine the market price of the reference obligation.

right to participate in distressed debt renegotiations that affect the going concern value of the firm. In this case, creditors who hold both the underlying obligation and the CDS contract – empty creditors as named by Hu and Black – may be indifferent to the firm's survival and reluctant to engage in value-enhancing behavior if a firm is in distress. This is a result of empty creditors' resistance to participate in out-of-court renegotiations. While out-of-court renegotiations would require empty creditors to make concessions, they would receive full recovery in default (e.g., bankruptcy, liquidation) from their CDS contracts. Therefore, while an economically viable but financially distressed firm would be better off by restructuring the distressed debt through out-of-court renegotiations, empty creditors may resist such renegotiations in order to benefit from their CDS contracts. The empty creditor hypothesis suggests that in the extreme case, over-insured creditors may even push economically feasible firms into costly bankruptcy by making renegotiations harder, and eliminate efficient restructuring.

A research note published by ISDA (Mengle, 2009) questions the validity of empty creditor hypothesis. Mengle (2009) reports no difference in the proportion of firms conducting out-of-court restructurings relative to filing for bankruptcy across firms with and without CDS. Bedendo, Cathcart, and El-Jahel (2012) support Mengle's findings. Contrary to the empty creditor hypothesis, the authors find no evidence for increased probability of filing for bankruptcy in the presence of CDS. They show that other precipitating factors such as leverage and short-term debt ratios determine the choice of restructuring method.

Given severe holdout problems in restructuring public debt, out-of-court restructuring of public debt take the form of a distressed exchange (Gilson, John, and Lang, 1990). Narayanan and Uzmanoglu (2014) study how firms design distressed exchanges so that they avoid possible resistance posed by empty creditors. They show that firms with CDS contract around hedged creditors by restructuring debt held by other creditors. Danis (2013) analyzes distressed exchange participation rates and shows that creditors in firms with CDS participate less in restructurings – also providing support for the economic role of CDS in distressed debt workouts. Subrahmanyam, Tang, and Wang (2014) study the propensity of credit rating downgrade and the probability of bankruptcy at CDS inception. They find that firms' credit risk increases after the inception of CDS trading. They argue that the increased credit risk is due to the reluctance of empty creditors to restructure debt. Peristiani and Sarino (2011) report a significant correlation between corporate distress and CDS in the recent years. They use a linear probability model as a proxy for CDS exposure to explain implied default rates. Utilizing a hazard model and Merton's contingent claims method, the authors find that firms with CDS had a greater probability of default during 2008.

On the other hand, CDS may provide benefits to creditors. Hedged creditors have stronger bargaining power in negotiations that may enhance their ability to extract greater concessions in renegotiations. Greater creditor control may also deter debtors from behaving opportunistically. In their theoretical framework, Bolton and Oehmke (2011) show that stronger creditors may reduce the probability of strategic default by tilting bargaining power from debtors to creditors.

In this paper, we analyze whether the frictions CDS introduce in renegotiation affect ex-ante bond prices through their effect on ex-post default and renegotiation decisions.

2.3 Hypothesis development

Creditors' ability to influence debt renegotiations depends on their relative bargaining power. In order for CDS to present renegotiation frictions, creditors should hedge a significant portion of their economic exposure to default risk in the CDS market. Therefore, the variable of interest is not simply a dummy variable indicating whether hedged creditors exist; it is rather a CDS exposure measure that proxies the proportion of creditors that also hold CDS contracts.

Davydenko and Strebuleav (2007) show that the strategic actions may affect credit spreads. If greater CDS exposure alters the balance of bargaining power between the debtor and creditors, the credit spreads should react in predictable ways. The following sections discuss these predictions.

2.3.1 The net effect: Costs vs. Benefits

Davydenko and Strebuleav (2007) identify two channels through which strategic behavior may influence credit spreads: bargaining in renegotiations and strategic default decision. As explained earlier, out-of-court renegotiations in the presence of creditors with CDS become harder – making costly default more likely.[2] In this case, higher CDS exposure should increase credit spreads because renegotiation frictions increase the probability of default and reduce the expected recoveries.

On the other hand, Davydenko and Strebuleav (2007) show that the prospects of a strategic default increase credit spreads. In a strategic default, the debtor behaves opportunistically and demands concessions from creditors even though the debtor possesses the resources to make payment on its obligations. This is because the prospects of debt reduction through renegotiations give debtors incentives to threaten creditors with default (e.g., Hart and Moore, 1994, 1998; Anderson and Sundaresan, 1996; Fan and Sundaresan, 2000; Favara, Schroth, and Valta, 2012). Creditors with lower bargaining power would agree to make concessions knowing that the pay-off would be even lower had the claims been restructured through default (e.g., bankruptcy, liquidation). In this case, CDS exposure may strengthen creditors' hand in

[2] Because default triggers payment on the CDS contracts, creditors with CDS become ordinary creditors after a firm is in default.

renegotiations by ensuring full recovery in default, and benefit creditors by allowing them to deter strategic default. Hence, credit spreads should decrease as creditors' CDS exposure increases.

This section shows that the net effect of CDS exposure on credit spreads is an empirical question. The following two sections develop a framework to study when the effects of CDS exposure on credit spreads are more pronounced.

2.3.2 Liquidation cost

In this section, we discuss the influence of CDS exposure on credit spreads when liquidation costs are higher. According to Davydenko and Strebuleav (2007), liquidation costs may affect credit spreads in two opposing ways.

First, creditors of firms with higher liquidation costs face greater losses in default since the recovery rates in default would be lower for these firms. If creditors' CDS exposure creates renegotiation frictions and increases the probability of default, then the expected bond recoveries should decline. Hence, creditors' CDS exposure should increase credit spreads more so as liquidation costs increase.

Second, because creditors face a threat of lower recovery in default, higher liquidation costs also increase the debtors' incentives to strategically default. Expecting a lower recovery in default (due to high liquidation costs), creditors would be less likely to call debtors' bluff for strategic default. In this case, creditors' CDS exposure should strengthen creditors' bargaining power, decrease the probability of strategic default, and therefore decrease credit spreads as liquidation costs increase.

Therefore, the net effect of creditors' CDS exposure on credit spreads when liquidation costs are higher is an empirical question.

2.3.3 Debtor bargaining power

In this section, we discuss how creditors' CDS exposure may influence credit spreads when debtor bargaining power is higher. Davydenko and Strebuleav (2007) explain how debtor bargaining power may affect credit spreads.

First, strategic default becomes more likely if debtors have greater bargaining power. In this case, if creditors' CDS exposure increases creditors' bargaining power, higher CDS exposure should lower the incidence of strategic default, and this effect should be more pronounced when debtors have greater bargaining power. Hence, we expect that creditor's CDS exposure reduce credit spreads more so as debtor bargaining power increases.

Second, creditors gain less from renegotiations when debtors are stronger. Hence, credit spreads increase when debtor bargaining power is higher. If CDS increase creditors' bargaining power, then creditors' CDS exposure should benefit them more when debtor bargaining power is higher – lowering credit spreads.

Therefore, we expect that creditors' CDS exposure will decrease credit spreads more so when debtor bargaining power is higher.

3 Data, sample selection, and empirical design

3.1 Data and sample selection

The majority of CDS contracts reference a senior unsecured bond. We confirm this in the CDS databases maintained by Bloomberg and Credit Market Analysis (CMA) and by identifying the seniority of 100 randomly selected CDS reference obligations from the Markit's Reference

Entity Database (RED) Codes.[3] Therefore, we limit out our attention to senior unsecured bonds.

We screen Bloomberg's bond database for senior unsecured bonds outstanding between October 2008 and December 2012. We start our analysis in October 2008, since it is when our proxy for CDS exposure – the net notional variable – becomes available.[4] We end our analysis in December 2012 due to the availability of financial data. While searching for bonds, we include only fixed and zero coupon bonds with no embedded options (plain vanilla bonds), keep only USD denominated bonds issued in the U.S. (e.g. series Regulation-S bonds), exclude bonds issued by financial firms and eliminate private placement bonds (e.g. series 144A bonds).[5] We keep only plain vanilla bonds to reduce the difficulties in spread estimations due to embedded options and/or variable coupon securities, and we remove the financial firms since their capital structure and method of debt renegotiations are relatively different from those of industrial firms. We eliminate private placements as their security characteristics such as liquidity and investor base differ from those of public bond issues. This bond search procedure results in 1,977 bonds issued by 231 firms at the ultimate parent company level. The Appendix shows the details of sample selection and the reduction in the number of observations due to each selection criteria.

Next, we obtain the financial information for our sample firms. We are able to match CRSP identification number (PERMNO) and COMPUSTAT identification number (GVKEY) for 221 out of 231 firms in our sample. The financial information and S&P long-term issuer ratings come from COMPUSTAT, the historical stock prices are downloaded from CRSP, and bond details are from Bloomberg. We exclude 6 more firms because they are classified as financial firms based

[3] We confirm the reference obligation class via Bloomberg that uses the RED Pair Codes for identification. RED Codes can also be viewed on Bloomberg.
[4] See section 3.2.3 for a detailed definition and source of the net notional data.
[5] Financial industry is excluded from the search results using Global Industry Classification Standard (GICS).

on their SIC codes (SIC codes: 6000-6999), resulting in a sample of 215 firms.[6]

We identify the firms with outstanding CDS contracts using the CDS ticker symbols from Bloomberg. Bloomberg reports the universe of RED Code matched reference firms under *CDSD* function. RED codes link the underlying CDS reference obligations with the CDS contracts and they are widely used as a standard identifier among traders to electronically match and confirm CDS transactions. We confirm that all of the U.S. reference entities from the Depository Trust and Clearing Corporation (DTCC)'s most actively traded 1,000 reference entities list are available in the Bloomberg CDS reference entity ticker database. We match the bond issuers and the CDS reference entities at the ultimate parent level. A firm's bonds are aggregated under the ultimate parent *only* if the two firms are associated prior to October 2008 and the ultimate parent is also the guarantor.[7] This procedure ensures that bonds' credit spreads reflect the default risk and strategic behavior associated with the underlying firm characteristics. We find that 169 out of 215 firms in our sample have CDS contracts outstanding.

Moving forward, we include a firm in the sample only if it has a CDS contract outstanding. This study focuses on firms with CDS because our hypotheses depend on CDS exposure, which is conditional on a firm having an outstanding CDS. In addition, the majority of the firms in our senior unsecured bond sample have CDS contracts. The heavy representation of the CDS firms in our sample does not allow for a comparison between CDS and non-CDS firms.

We next estimate credit spreads using zero-volatility spread (z-spread) because z-spread takes into account the term structure of benchmark interest rates. Davydenko and Strebuleav (2007) show that z-spread is more appropriate in measuring credit risk than the nominal yield spread (yield-to-maturity minus risk-free rate). We compute z-spread by solving the following equations

[6] The bond screening criterion for the financial sector in Bloomberg is based on GICS industry classification.
[7] We confirm the guarantor information by using the bond and CDS tickers of the parent and the subsidiary.

for z:

$$P + AI = \sum_{n=1}^{N} c(n) \frac{1}{\left(1 + \frac{r_{fn}}{per} + \frac{z}{per}\right)^{(n_0+n-1)}} \qquad (1)$$

$$n_0 = \left(\frac{pdate - cdate_{last}}{cdate_{next} - cdate_{last}}\right) \qquad (2)$$

$$AI = n_0 \frac{c}{per} FV \qquad (3)$$

$$c(n) = \frac{c}{per} FV \qquad (4)$$

$$c(N) = \left(1 + \frac{c}{per}\right) FV \qquad (5)$$

where P is bond price, AI is accrued interest, n is coupon period, $c(n)$ is dollar amount of coupon in period n, per is annual coupon periodicity, r_{fn} is risk-free rate corresponding to coupon period n, z is z-spread, n_0 is number of accrued years, $pdate$ is observation date, $cdate_{last}$ is last coupon, $cdate_{next}$ is next coupon date, c is percentage annual coupon rate, and FV is face value of the bond.

We obtain bond prices from Bloomberg and we only use prices provided by TRACE data source to ensure that the price used in spread calculations is from an actual transaction.[8] We use zero-coupon Treasury curve from Bloomberg as the risk-free rate. Zero-coupon Treasury curve

[8] Other pricing sources that we have access to (e.g., BGN, BFV, and BVAL) are matrix prices that may bias the spreads calculations.

reduces the coupon effects associated with the coupon rate of the Treasury bonds.[9] These curves are available in 15 different maturities spanning from 3-months to 30-years. We linearly interpolate zero-curves to identify maturity matched risk-free rates. During our analysis period, we are able to compute a total number of 264,831 daily z-spreads for 778 bonds issued by 158 out of 169 firms in our sample.

We further screen our sample of 158 firms for the differences in firm/bond characteristics that may contaminate the empirical analysis. We drop bonds with remaining maturities less than 1 or more than 30 years as of the trade date to reduce the noise in credit spread calculations. As Davydenko and Strebuleav (2007) mention, small price measurement errors may result in large credit spread deviations for bonds with very short maturities. The spread estimates for bond maturities greater than 30-years is also problematic because of the difficulty with finding a benchmark risk-free rate with an identical maturity. We also require firms to have stock prices available at least 1 year preceding the trade date. This eliminates any performance bias due to recent IPO firms and allows for calculating asset volatility using equity returns in the past year, which we discuss in section 3.2.1. These screening steps result in a sample of 150 firms.

Finally, we keep 123 firms (621 bonds) out of 150 firms (742 bonds) that have an investment grade credit rating (credit rating above or equal to BBB-). Analyzing the investment grade firms is motivated by several reasons. First, we would like to focus our analysis on the default component of bond yields and minimize the influence of other frictions, such as liquidity. Chen, Lesmond, and Wei (2007) show that liquidity can explain a lower variation in bond yields for investment grade bonds compared to the speculative grade bonds. Second, Blume, Keim, and Patel (1991) show that high-yield bonds behave like both bonds and stocks. The primary purpose

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[9] Bloomberg constructs Treasury zero-curves using a bootstrapping methodology and store them under I025 index. For example, the function for 3-month Treasury zero-curve is I02503M <Index>.

of this study is to capture the influence of CDS from the creditors' perspective as the creditors price the strategic actions of the debtor. A sample of investment grade firms better allows for capturing this sensitive information. Third, because we control for the probability of financial distress by calculating an implied asset volatility measure using Merton's (1974) structural model, our distress measure better fits the investment grade firms. Teixeira (2007) shows that Merton's model performs better in investment grade bonds. Therefore, analyzing investment grade firms allows us to control for the default component of bond yields more accurately and, as a result, identify the renegotiation frictions associated with CDS exposure.

Table 1 reports that the final sample consists of 194,654 daily credit spreads provided by 123 firms (140 firm and credit rating combinations). Panel A in Table 1 shows the average credit spreads by each credit rating. Panel A reports that AAA rated bonds have the lowest average credit spread of 84.74 bps. The spreads increase monotonically as ratings get lower with a maximum of 304.76 bps for the BBB rated bonds. The variation in spreads also increases as the ratings decline. The standard deviation of ratings is around 69 bps for AAA and AA rated bonds, whereas BBB rated bonds' credit spreads have a standard deviation of 253 bps. A higher variation in credit spreads for lower rated firms is expected since the heterogeneity among firms' quality increases as the credit ratings decline. Panel B in Table 1 reports the spreads averaged at each firm and credit rating level and shows that the average spreads by firm and credit ratings are higher than those in Panel A.

Consistent with Davydenko and Strebuleav (2007), A and BBB rated firms dominate the sample. Of the 140 firm and credit rating combinations, 5 are AAA, 13 are AA, 49 are A, and 73 are BBB rated. The time-to-maturity for the entire sample is around 9.5 years, comparable to 9.43 years reported by Davydenko and Strebuleav (2007). The credit spreads in our sample are considerably higher than the spreads reported in Davydenko and Strebuleav (2007) that study a period from 1994 to 1999. This is because our sample period from 2008 to 2012 coincides with the end of the financial crisis of 2008. The credit spreads were higher during this period as the industrial firms became riskier while the benchmark risk-free interest rates were close to zero.

3.2 Variables

3.2.1 Credit risk variables

We mainly use the credit risk variables discussed in Davydenko and Strebuleav (2007). Research in recovery rates also provide guidance on variables that may also influence credit spreads. For instance, Cangemi, Mason, and Pagano (2012) show that asset volatility and discount rate are critical for understanding the dynamics of recovery in default. We closely follow the methodology of Davydenko and Strebuleav (2007) to conduct our empirical tests, and hence, we primarily use their variables.

We use leverage, time-to-maturity, natural log of market value of equity, asset volatility, and risk-free rate as the fundamental credit risk variables.[10] In addition, we use natural log of bond trading volume to control for liquidity component of credit spreads (e.g., see Chen, Lesmond, and Wei, 2007). Following Davydenko and Strebuleav, we calculate leverage as the ratio of total debt to the market value of assets. Total debt is from COMPUSTAT (*dlc* + *dltt*) and the market value of assets is the sum of market value of equity from CRSP (*prc x shrout*) on the trade date and total debt. Table 2 shows that the mean leverage is 27.88% with a median of 24.14%. Leverage shows considerable variation across firms. Time-to-maturity is in years as of the trade date and the maturity date is from Bloomberg. Table 2 shows that the average maturity of a firm's bonds is 9.31 years and the sample's standard deviation of bond maturity is 5.24 years.

[10] We use log(market value of equity) to control for size instead of log(assets), because log(market value of equity) has greater time series variation and it is less correlated with other explanatory variables as compared to log(assets).

Total assets are from COMPUSTAT (*at*). The average total assets and market value of equity are \$45.54 billion and \$38.85 billion, respectively. Our sample firms are almost twice as large as Davydenko and Strebuleav's sample, confirming that CDS contracts are available for larger firms.

We use weekly bond volume as a proxy for bond liquidity. Intraday bond volume is from TRACE (variable *ascii_rptd_vol_tx)*. TRACE reports +1MM and +5MM for intraday quantities exceeding 1,000,000 and 5,000,000, respectively. We assume that these figures represent the lower bound of their quoted volume (1,000,000 and 5,000,000) and aggregate the intraday volume for each bond during the week matching the credit spread observation date. We take the natural logarithm of the volume in order to reduce the impact of bonds with extremely large trading activity and reduce the influence of aforementioned lower bound assumption.

Asset volatility controls for the default risk of a firm. Since asset volatility is not observable, we estimate it using Merton's (1974) structural model following the methodology presented by Bharath and Shumway (2008).

Briefly, Merton (1974) assumes that a firm's value follows a geometric Brownian motion:

$$\frac{dV}{V} = \mu dt + \sigma_V dW \tag{6}$$

where V is the value of firm's assets, μ is the drift term for the entire firm, σ_V is the asset volatility, and dW is a Wiener process. Accordingly, the value of equity can be presented as a call option on the firm:

$$E = VN\left(d_1\right) - \exp(-rT)FN\left(d_2\right) \tag{7}$$

$$d_1 = \frac{\ln\left(V/F\right) + \left(r + 0.5\sigma_V^2\right)T}{\sigma_V\sqrt{T}} \tag{8}$$

$$d_2 = d_1 - \sigma_V\sqrt{T} \tag{9}$$

where E is the market value of equity, r is the risk-free rate, F is the value of debt, and T is the maturity of debt issue. In this model, all of the variables except for V and σ_V are observed, which renders the application of an iterative approach that simultaneously solves Equation 7 for the missing variables using a starting value of σ_V.

Daily market value of equity (E) is from CRSP (*prc x shrout*), time-to-maturity (T) is one-year and risk-free rate (r) is T-bill rate from Kenneth R. French's web site.[11] The value of debt (F) is an important input to the model as it determines the default point. A firm will default if its asset value goes below this debt level. Crosbie and Bohn (2002) explain that the default point lies between the total debt and short-term debt. This approach gives short-term debt greater importance in the model. Eom, Helwege, and Huang (2004) discuss that this is logical since shorter-term debt is more likely to cause a default. They compare various structural models of default risk and run a sensitivity analysis on the leverage assumptions used in their models. They show that, compared to using total debt as the default point, giving greater weight to short-term debt reduces the estimated spreads, but better fits their data. Vassalou and Xing (2004) also use the same approach in estimating the default point. They argue that long-term debt should have a lower weight in determining the default point because it reduces a firm's default risk by increasing its ability to roll over its short-term debt. Therefore, we also assume that the default point is the sum of short-term debt (COMPUSTAT *dlcq*) and one half of long-term debt

[11] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html

(COMPUSTAT 0.5 x *dlttq*). Accordingly, firm value (V) is the sum of E and F.

Following Bharath and Shumway (2008), we take an initial starting value of $\sigma_V = \sigma_E[E/(E + F)]$ where σ_E is the annualized standard deviation of equity returns and solve for V in Equation 7 for every day during the year prior to the trade date. Then, we calculate the asset volatility using the estimated asset values and solve for V in Equation 7 using the asset volatility estimated in the second stage. This process is repeated until the asset volatility converges at 0.001 level.[12] Table 2 reports that the average asset volatility for our sample is 30.18% with a median of 30.26%. Asset volatility for our sample is smaller than 56.00% mean and 46.32% median values reported by Bharath and Shumway (2008). This is not surprising as the average market value of equity for their sample is $1.07 billion that is much smaller than $38.85 billion for our sample. Larger firms are likely to have lower asset volatility.

3.2.2 Liquidation cost and debtor bargaining power variables

A proxy for the liquidation cost is important for estimating the recovery in default. If liquidation costs are higher, then creditors would expect to have lower recoveries in default. Following Davydenko and Strebuleav (2007), we use non-fixed assets as a proxy for liquidation costs. We calculate non-fixed assets as one minus the ratio of net PP&E (COMPUSTAT *ppent*) to the book value of assets (COMPUSTAT *at*). PP&E represents the tangible assets that tend to have a greater liquidation value. Hence, as PP&E divided by the book value of assets declines, non-fixed assets variable increases, and accordingly liquidation costs rise. Table 2 reports that the average non-fixed assets for our sample firms is 61.97%. In addition, we use a broader proxy for liquidation costs using the tangibility measure developed by Almeida and Campello (2007). Accordingly, we define intangibility as {1 – [Cash and Equivalents (COMPUSTAT *che*) + Receivables (COMPUSTAT *rect*) + 0.547 x Inventories (COMPUSTAT *invt*) + 0.535 x PP&E

[12] Stop the iteration if $(\sigma_{V(j)} - \sigma_{V(j-1)}) \leq 0.001$ where j is the number of iterations.

(COMPUSTAT *ppent*)]/Assets (COMPUSTAT *at*)}. Intangibility measures the proportion of assets that cannot be pledged. As asset pledgeability declines, recovery rates decline, and liquidation costs rise.[13] Table 2 shows that average intangibility is 58.49% with a median value of 56.88%.

Following Davydenko and Strebuleav (2007), we use CEO and managerial shareholding as a proxy for debtor bargaining power. As the managers have greater ownership in the form of stocks, their incentives would be more in line with the shareholders'. The executive compensation data comes from ExecuComp database. Managerial shareholding is the ratio of the aggregate number of shares held by the highest paid five executives to the total number of shares outstanding. Table 2 reports that the average CEO shareholding is 0.53% and the average managerial shareholding is 0.88% for our sample firms. Davydenko and Strebuleav (2007) report that the average CEO ownership and managerial ownership for their sample are 0.93% and 1.73%, respectively. Larger size of the firms with CDS contracts may explain the relatively smaller managerial equity ownership reported for our sample. Average book value of assets is \$7.81 billion in Davydenko and Strebulaev's sample whereas it is \$45.54 billion in our sample.

3.2.3 CDS exposure variable

We use net notional as a proxy for the total amount of outstanding CDS contracts for a given firm. Net notional is the net amount of CDS contracts bought by protection buyers on a single name reference entity (firm). This is the aggregate protection bought from all counterparties and hence represents the outstanding dollar amount of credit protection. Net notional data is provided with the courtesy of DTCC and available weekly since October 2008 for the most actively traded 1,000 reference entities. Net notional is available for 81% (88%) of firms (credit spreads) in our sample. Assuming that missing net notional values are equal to zero, Table 2 reports that the

[13] Hahn and Lee (2009) also use this intangibility measure in a different context.

average net notional for our sample firms is $1.00 billion.

In order to construct a CDS exposure variable, for each firm, we calculate a *net notional/total debt* variable as the dollar amount of net notional outstanding for a firm divided by the same firm's total debt outstanding. Net notional/total debt variable assumes that all creditors of a firm may have an interest in purchasing a CDS contract. As an alternative CDS exposure measure, we construct a variable based on the CDS reference debt. Since senior unsecured debt is the most widely used reference obligation as discussed in section 3.1, we use the amount of net notional divided by total senior unsecured debt as an alternative CDS exposure variable. We download the debt structure for firms from Capital IQ database. We name this variable *net notaional/sen. unsec. debt* and replicate the results using this variable as robustness in section 4.2.

Given that some firms in our sample does not make into the DTCC's most actively traded 1,000 reference entities list, we assume that CDS exposure is equal to zero when net notional is unavailable. This assumption implies that these firms with missing net notional do not have sufficiently large number of hedged creditors to influence their debtor-creditor relationships. We find that firms with missing net notional are larger and have more leverage than the smallest firm in the DTCC's list. This indicates that *net notional/total debt* for firms with missing net notional is likely to be lower than that of firms with net notional data. For robustness purposes, in section 5.2 we replicate the analysis by dropping the observations with missing net notional data.

Table 2 shows that the average net notional/total debt is 20.14% with a standard deviation of 25.27%. This indicates that over-insurance is likely as three-standard deviation increase in normalized net notional results in 95.95% CDS exposure, close to 100%. Table 2 shows that the average net notional/sen. unsec. debt for our sample is 26.18% with a standard deviation of 33.65%. If senior unsecured creditors are the only creditors purchasing CDS contract, even two standard deviation increase in net notional/sen. unsec. debt implies that 93.48% of the amount of outstanding senior unsecured debt may be protected by CDS contracts. Therefore, creditors may possibly be over insured in some circumstances.

Table 3 reports a correlation matrix of the variables of interest. CDS exposure (net notional/total debt) is positively correlated with asset volatility, time-to-maturity, and risk-free rate, and negatively correlated with log(m.v. equity) and log(1+bond volume). The correlation table implies that smaller and riskier firms with illiquid and longer maturity bonds are associated with higher CDS exposure. Interestingly, CDS exposure has zero correlation with leverage, suggesting that the demand for credit insurance is more related with uncertainty (volatility of the assets) than the default triggering point (leverage). CEO shareholding and managerial shareholding show a strong correlation (0.94). Non-fixed assets and intangibility are also strongly correlated with a correlation coefficient of 0.45. Hence, each variable within the liquidation cost and debtor bargaining power categories can be used as a substitute for one another while controlling for slightly different aspects of the economic behavior they measure.

3.3 Empirical methodology

We follow Davydenko and Strebuleav (2007)'s sample selection and empirical methodologies to eliminate the influence of large firms with multiple bonds to the sample and capture the firm level characteristics that contribute to credit spreads in a regression framework.

We construct a regression sample by randomly selecting only one credit spread from each firm in each week during the entire period from October 2008 to December 2012. This approach helps with capturing the firm level effects and reduces the impact of unbalanced nature of the data structure. Table 4 reports the distribution of credit spreads for the randomly selected regression sample.

Panel A in Table 4 shows that there are 16,774 unique spreads in the regression sample. Panel B in Table 4 reports the average spreads at the firm and credit rating levels. The monotonic relationship between the credit ratings and the spreads persists in the regression sample. Table 3 shows that net notional data is available for the majority of the sample: 88% of the total number of credit spreads and 81% of the firms in the regression sample have net notional data. While the random selection method reduces the influence of firms with multiple bonds outstanding, it creates a noise in credit spread estimations. In addition, it does not allow for making inferences about the cost of funding, as randomly selected bonds may not represent the cost of the entire class of debt. Therefore, we also use a weighted-average credit spreads as an alternative dependent variable where the weights represent the issue size of each bond issued by the same firm.[14]

Table 4 also reports the statistics for net notional/total debt variable by credit ratings. We find that average CDS exposure for our sample firms is around 20% and increases as credit ratings deteriorate.[15] Panel A shows that AAA rated firms have an average of 4.18% CDS exposure while it is 28.19% for BBB rated firms. There is considerable variation in CDS exposure in each credit rating class with a standard deviation of 25% for the entire sample. The monotonic relationship between credit ratings and CDS exposure raises endogeneity concerns that we address in section 4.3.

Following Davydenko and Strebuleav (2007), we run weekly cross-sectional regressions as in Fama and MacBeth (1973), and report the time series averages of the coefficient estimates with Newey-West adjusted standard errors. This regression approach controls for the time series

[14] See Section 4.2 for the details.
[15] Net notional/total debt is around 25% when observations with zero net notional are excluded from the sample.

variation in the coefficient estimates. Alternatively, methods such as random and fixed effects panel regression models, and pooled regression with cluster corrected standard errors and time dummies do not reasonably fit our data structure. Fixed effects model is not appropriate as the majority of firm characteristics of interest are fixed and some explanatory variables have small variation through weeks given the short analysis period. Random effects model would suffer from possible correlation between the explanatory variables and the random part. Finally, the pooled regression approach with time and firm fixed effects is not appropriate because time and firm dummies would reduce the degrees of freedom given the relatively small sample size. Alternatively, using cluster corrected standard errors in a pooled OLS would result in significant efficiency losses due to the long panel data structure (Number of observations in clusters is greater than the number of clusters). We also replicate our main results using fixed-effects regression and pooled OLS regression with cluster corrected standard errors methodologies, but do not tabulate the results for brevity.

3.4 Hypotheses testing

The hypotheses outlined in section 2.3 show that credit spreads reflect both the costs and benefits associated with CDS contracts. Since these effects have inverse signs, the significance and sign of the coefficient estimate on CDS exposure when explaining credit spreads would represent the net effect of CDS exposure on credit spreads. This regression should control for the fundamental credit risk variables, credit ratings, and industry fixed effects to extract the marginal contribution of CDS exposure on the credit spreads. Following cross sectional regression equation is the base model for testing the net effect of CDS on credit spreads:

$$Spread_i = \alpha + x_i^{'}\beta^{Credit} + CDS_i\beta^{CDS} + \varepsilon_i \quad (10)$$

where $Spread_i$ is credit spread on firm i, x_i' is a row vector of credit risk variables including credit rating and industry dummies, β^{Credit} is a column vector of coefficient estimates on the credit risk variables, CDS_i is CDS exposure of firm i, β^{CDS} is the coefficient on CDS exposure, and ε_i is the error term. We report and interpret the time series averages of the individual coefficients from weekly cross sectional regressions with Newey-West adjusted standard errors.

The coefficient estimate on CDS exposure (β^{CDS}) should reflect two counter effects: (1) the costs of inefficient liquidation – Positive, and (2) the benefits of deterring strategic default – Negative. If the coefficient estimate is significant, then the sign should reveal which effect dominates in practice. On the other hand, an insignificant beta coefficient would mean that CDS exposure is empirically irrelevant.

We use the interaction of CDS exposure with liquidation cost and debtor bargaining power variables to test the liquidation cost and debtor bargaining power predictions. This interaction term captures the influence of CDS exposure as the corresponding interacting variable rises. Using a multiplication of variables (e.g., A x B) as an interaction term and the underlying variables themselves in the same model causes a multi-collinearity problem. Davydenko and Strebuleav (2007) deal with this issue by using one set of variables in the base model and including the interaction of an alternative pair of variables in the same regression. This way the multi-collinearity declines while reserving the multiplicative effect in the model. In our case, however, there is only one measure of CDS exposure.[16]

To address this issue, we first run a regression where the interaction term (e.g., A x B) is the dependent variable and components of the interaction term (e.g., A and B) are the explanatory

[16] While we use net notional/sen. unsec. debt as an alternative proxy for CDS exposure, it primarily varies by the weekly variations in net notional. Hence, net notional/total debt and net notional/sen. unsec. debt are highly correlated. Using these alternative CDS exposure proxies do not cure the multi-collinearity concerns.

variables, and then use the residual from this model as the interaction term. The residuals are, by definition, orthogonal to the explanatory variables and expected to reduce the multi-collinearity problem in the base regression. Accordingly, the following cross sectional regression summarizes the regression model for testing the liquidation cost and bargaining power hypotheses:

$$Spread_i = \alpha + x_i^{'}\beta^{Credit} + CDS_i\beta^{CDS} + LQ_i\beta^{LQ} + BP_i\beta^{BP} + INT_i\beta^{INT} + \varepsilon_i \tag{11}$$

where LQ_i is the liquidation cost variable for firm i and β^{LQ} is its coefficient estimate, BP_i is the debtor bargaining power variable for firm i and β^{BP} is its coefficient estimate, INT_i is the residual from the interaction regression of interest and β^{INT} is its coefficient estimate, and ε_i is the error term. We interpret the sign and significance of β^{INT} to test the liquidation cost and debtor bargaining power hypotheses.

4 Results

4.1 The net effect: Costs vs. Benefits

Regression I in Table 5 reports the coefficients for the credit risk variables. This base model controls for the default component of credit spreads.

Consistent with the literature, leverage, asset volatility, and time-to-maturity are all positively, whereas risk-free rate, log(m.v. equity) and log(1+bond volume) are negatively related with credit spreads. The base model fits credit spreads data well as it explains 68% of the variability in the credit spreads. Davydenko and Strebuleav (2007) report an R^2 of 32% for a similar model explaining credit spreads. We are able to achieve a higher R^2 because, different from Davydenko and Strebuleav (2007), we also control for industry and rating fixed effects that have significant explanatory power.

Regression II in Table 5 formally tests the net effect of CDS on credit spreads by adding net notional/total debt variable in the base regression as a proxy for CDS exposure. The coefficient estimate on net notional/total debt is 0.48 and it is statistically significant.[17] Hence, there is evidence that CDS related costs of inefficient restructuring outweigh its benefits of deterring strategic default. One standard deviation increase in the firm level CDS exposure (25%) results in a 12 bps increase in credit spreads.

Regression III in Table 5 controls for the unobservable effects of having net notional data. Firms with net notional information – firms reported in the 1,000 most actively traded reference entity list – have, on average, higher credit spreads than those that are inactive in the CDS market by 21.10 bps. The coefficient estimate on net notional/total debt is 0.37 – a positive and significant coefficient also confirms that the costs dominate the benefits. Since average net notional/total debt for non-missing net notional observations is 25%, these coefficient estimates suggest that average firm experiences around 30 bps increase in credit spreads due to creditors' CDS exposure. The impact of CDS exposure for an average firm in our sample is marginally economically significant after accounting for transaction costs since Schultz (2001) reports that the transaction cost in the corporate bond markets is about 27 bps. CDS exposure may impose significant economic costs for some of our sample firms since there is considerable variation in net notional/total debt variable: the standard deviation of net notional/total debt is about 25%. In the extreme, CDS exposure of 100% translates into higher credit spreads by 58 bps. This finding is consistent with Bolton and Oehmke (2011) as the authors propose that over insurance may give rise to higher credit spreads through higher incidence of a default.

[17] Fixed-effects regressions with time-dummies predict a coefficient estimate of 0.58 (significant at 1% level), and pooled OLS regression with clustered standard errors result in a coefficient estimate of 0.66 (significant at 5% level).

4.2 Robustness tests

We run several robustness tests to confirm the influence of CDS exposure on credit spreads reported in the earlier section. These tests include using an alternative CDS exposure variable, accounting for the simultaneity issues between credit spreads and CDS exposure, controlling for the influence of observations without net notional observations, and investigating the potential bias arising from randomly selecting weekly credit spreads as the dependent variable.

First, we use *net notional/sen. unsec. debt* as an alternative proxy for CDS exposure. Given that senior unsecured debt is the reference obligation for the majority of the CDS contracts, using the amount of net notional divided by senior unsecured debt may provide insights about the possibility of over-insurance and its impact on the funding costs. We replicate the baseline results reported in Regression II of Tables 5 using net notional/sen. unsec. debt as a proxy for CDS exposure. Regression I in Table 6 reports the results. The coefficient estimate on net notional/sen. unsec.debt is 0.44 and significant. Since net notional/sen. unsec. debt has a standard deviation of 34%, one standard deviation increase in net notional/sen. unsec. debt results in a 15 bps increase in credit spreads. Therefore, the baseline results are robust to the choice of CDS exposure proxy.

Second, we account for potential simultaneity issues. CDS exposure may reflect investors' expectations about future credit spreads. Creditors that predict future downturns in credit quality may purchase credit insurance in advance or simultaneously with increasing credit spreads. In this case, predicting credit spreads at the same time with CDS exposure may result in a spurious relation and explain little about the effect of empty creditors. We dissect the simultaneity by using lagged variables of net notional/total debt. If lagged net notional/total debt is insignificant, then this would indicate that indeed investors' expectations about future credit quality derive the earlier findings. On the other hand, if lagged net notional/total debt maintains its significance, then it is more likely that creditors' CDS exposure explains the positive association between the CDS exposure and credit spreads.

We use three-month lagged net notional/total debt measured starting one week prior to a trade date as an alternative measure of CDS exposure since it is unlikely that CDS exposure can predict credit spreads three-months in advance of the security prices.[18] Regression II in Table 6 replicates Regression II in Table 5 using lagged net notional/total debt as a proxy for CDS exposure. The coefficient estimate on the CDS exposure is 0.50 and statistically significant.[19] These results imply that possible forward-looking credit risk information in CDS exposure does not derive our main results association with CDS exposure.

Third, we investigate whether observations with missing net notional data influence our findings. As discussed in section 3.2.3, DTCC reports net notional for the most actively traded 1,000 reference entities. The majority of our sample firms (81%) and weekly credit spread observations (88%) are in the DTCC' list and. We assume CDS exposure for firms with missing net notional has limited influence in altering the renegotiation dynamics. While this assumption makes economic sense, it may introduce a measurement error. In order to understand the impact of the zero net notional assumption on the baseline results, we replicate the baseline results by dropping the firms without net notional. Regression III in Table 6 replicates Regression II in Tables 5 when we drop the observations without net notional data. We find that the coefficient estimate on net notional/total debt is 0.53 and it is still significant. Hence, the results are robust to the exclusion of observations without net notional data.

[18] Results are identical by using 6- or 12-month lagged CDS exposure.

[19] As alternative measures, we use mean and median normalized net notional measured prior to three-month before a trade date. In addition to alleviating possible simultaneity concerns, this approach also reduces the number of observations with missing net notional. The results are identical.

Finally, we test whether randomly selecting credit spreads bias our findings. As discussed in section 3.3, randomly selecting credit spreads when a firm has multiple bonds outstanding may create noise in estimating the firm level credit spreads. Hence, we replicate the baseline result reported in Tables 5 using weighted-average credit spreads as the dependent variable. For each firm and each week, we calculate a firm level weighted-average credit spreads measure where the weights represent the issue size of each bond for which credit spread is available. We also calculate a weighted-average time-to-maturity and log(1+bond volume) using the same weighting approach. Regression IV in Table 6 reports the results. Regression VI shows that the coefficient estimate on net notional/total debt is 0.53 and significant, which is similar to the coefficient estimate of 0.48 when the same regression model uses randomly selected credit spreads as the dependent variable. Hence, the results are robust to the selection method of credit spreads.

4.3 Endogeneity

Our baseline regressions control for the known determinants of credit spreads in order to understand the marginal effect of CDS exposure on credit spreads. However, our proxy for CDS exposure – net notional/total debt – may be correlated with credit spreads through channels other than the influence of empty creditors. Failure to account for these unobservable effects may result in biased coefficient estimates. While estimating credit spreads, the unobservable effects will be left in the error term because the prediction model does not account for endogeneity. Since the unobservable effects are correlated with CDS exposure, this will also lead to a correlation between the error term and CDS exposure, violating a basic assumption of the cross-sectional OLS regressions.

In order to address the potential for endogeneity, we follow a 2-stage instrumental variable

(IV) regression approach. We use two IVs: Markit's Investment Grade CDX Index notional amount and the affiliated institution's (lender and/or bond underwriter) foreign exchange hedging positions divided by their assets (FX/Assets).

Markit's Investment Grade CDX index (CDX index) is a tradable CDS index covering 100 North American investment grade companies. CDX index rolls semi-annually in March and September to ensure that the index constituents represent the most liquid segment of the CDS market. Liquidity is important for CDX index as it allows for trading credit index tranches, options, and default baskets. According to Markit, the family of CDX indices make up 40% of total CDS notional reported in DTCC. Therefore, once a firm is included in the index, index level trading activity is likely to affect the firm' net notional, but this variation in net notional is unlikely to be related with the underlying quality of the firm. We use natural logarithm of CDX index notional reported by DTCC as our first IV.

The second IV in our study is motivated by the literature in CDS research. Subrahmanyam, Tang, and Wang (2014) and Saretto and Tookes (2013) identify a firm's lenders and bond underwriters, and use their average foreign exchange (FX) hedging position as an instrument for the availability of CDS contracts. Subrahmanyam, Tang, and Wang (2014, p. 3) provide the intuition for this IV on "Lenders with a larger FX hedging position are more likely, in general, to trade the CDS of their borrowers". Using a similar approach, we identify the bond underwriters for each firm in our sample using Bloomberg. For identifying the lenders, we analyze the lending relationships of our sample firms within a five-year period prior to the observation date because Ioannidou and Ongena (2010) find that the median length of an observed lending relationship is approximately five years. We use Thomson Reuters Dealscan loan originations data to identify the lending relationships. We obtain the Dealscan-Compustat identifier link data from Michael R.

Rboerts' web-site (see Chava and Roberts, 2008 for the details on the construction of the data) .[20] For each loan, we use the lead arranger as the primary lender. We identify lead arrangers using the "LeadArrangerCredit" field. If a lead arranger is not identified for a loan, we follow the methodology of Cai, Saunders, and Steffen (2011) to find the lead arranger(s).

The affiliated institutions' FX positions and total assets at the bank holding level are from the Y9C reports maintained by the Federal Reserve. For each firm, we compute average lender and bond underwriter FX position divided by their total assets (FX/Assets) as an IV for CDS exposure. Accordingly, if the lenders and/or underwriters have greater FX position, they are more likely to be active in the CDS market – leading to greater CDS exposure. The lenders and/or underwriters' FX position is less likely to be related with credit spreads except through its correlation with the CDS exposure.

In the first stage, we predict net notional/total debt using our IVs. Net notional/total debt is subject to censoring as DTCC reports net notional for the most actively traded 1,000 reference entities. [21] We fit a Tobit regression model in the first stage to account for the data censoring.

To summarize a Tobit regression, assume that the model of interest is to estimate a latent net notional/total debt variable, y^*,

$$y^* = x_i^{'}\beta + \varepsilon_i \qquad (12)$$

where x_i is a 1xk vector of explanatory variables and an intercept, β is a kx1 vector of coefficient estimates, and ε_i is an error term distributed normally with a mean of zero and standard deviation

[20] http://finance.wharton.upenn.edu/~mrrobert/data_code.htm

[21] DTCC reports the 1,000 most active reference entities based on gross notional variable. We are, however, interested in net notional due to its economic relevance as a proxy for hedged creditors. We assume that firms with high gross notional also would have high net notional. Oehmke and Zawadowski (2011) show that on average net notional is 10% of gross notional while there is considerable variation.

of σ . Because y^* is censored, we instead observe y,

$$y=\begin{cases} y^* & if \;\; y^* > L \\ L & if \;\; y^* \le L \end{cases} \tag{13}$$

where L is the censoring point. Because the expected value of y is not equal to the expected value of y^* due to censoring, the estimation of the coefficients of interest renders using a maximum likelihood estimator. We maximize the following likelihood function:

$$\lambda = \prod_{i=1}^{n} \left[\frac{1}{\sigma} \phi\left(\frac{y_i - x_i^{'}\beta}{\sigma} \right) \right]^{d_i} \left[\Phi\left(\frac{L - x_i^{'}\beta}{\sigma} \right) \right]^{1-d_i} \tag{14}$$

where d_i takes the value of 1 if an observation is not censored, 0 otherwise, $\phi(\,)$ and $\Phi(\,)$ denote the probability density function and cumulative distribution function for a standard normal distribution. A challenge for our study arises because the censoring point for net notional/total debt is unknown. Carson and Sun (2007) show that when the censoring point is unknown, setting it to the minimum observable variable in the sample would result in consistent estimates. Hence, we assume that the lowest net notional/total debt for the values of net notional reported each week represents the threshold censoring point for that week.[22] We fit a Tobit regression model for each week and then predict the net notional/total debt for all firms. Reported in Table 7 are the averages of coefficient estimates from 218 cross-sectional regressions.

Regressions I and III in Table 7 report the first stage regression results for net notional/total debt using CDX index notional and FX/Assets as IVs, respectively. We find that both of our IVs

[22] Results are identical when net notional/total debt is censored at zero.

are positive and significant.[23] This implies that CDX index trading and lender/underwriter FX position are both strong IVs. Regression II and IV in Table 7 report the second stage regression results for the corresponding first stage regressions. The coefficient estimate on estimated predicted net notional/total debt is 0.31 in Regression II and 1.11 in Regression IV. Both of the coefficient estimates are statistically significant and they are comparable to the coefficient estimate of 0.48 as reported Regression II of Table 5. These results imply that the influence of CDS exposure on credit spreads is unlikely to be driven by endogeneity problems.

4.4 Liquidation cost

Regression models I and II in Table 8 test the liquidation cost hypothesis. The regression models include credit risk variables from regression I in Table 5, rating and industry dummies, but do not report them for brevity. Regression I uses intangibility and regression II uses non-fixed assets as a proxy for liquidation costs. The coefficient estimate on CDS exposure and liquidation cost interaction term is positive and significant in both of the regressions. Hence, these results show that the frictions (costs) associated with CDS exposure tend to have greater impact on credit spreads as liquidation costs increase.

4.5 Debtor bargaining power

Regressions III and IV in Table 8 analyze the debtor bargaining power hypothesis. The regression models include credit risk variables from regression I in Table 5, rating and industry dummies, but do not report them for brevity. The coefficient estimate on the interaction term between CDS exposure and managerial shareholding (CEO shareholding) is -0.25 (-0.14) and significant. Hence, there is evidence that the benefits associated with CDS exposure become greater when debtor bargaining power is higher. We empirically show that CDS exposure may create benefits in debt renegotiations as conjectured in the theoretical predictions of Bolton and

[23] IVs are also significant in the majority of the cross-sectional regressions.

Oehmke (2011).

5 Summary

CDS may alter the balance of bargaining power between the debtor and creditors, and affect distressed debt renegotiations. Bolton and Oehmke (2011) identify primarily two mechanisms through which CDS may have an economic impact on the underlying firms.

First, creditors hedged with CDS would be indifferent to a firm's survival and may raise the probability of default over renegotiations. Since renegotiations require accepting a recovery below par while default triggers payment on their CDS contracts and leads to a full recovery, hedged creditors may increase the costs of inefficient renegotiations by preferring a default to renegotiations.

Second, hedged creditors would have greater bargaining power in distress renegotiations since their CDS contracts promise full recovery in default. By making hedged creditors tougher in renegotiations, CDS may deter the debtor from behaving opportunistically in order to extract rents from the creditors. In other words, CDS may reduce the probability of strategic default, and hence create benefits for the creditors.

We follow the empirical methodology of Davydenko and Strebuleav (2007) and analyze bonds' credit spreads – the default risk component of bond yields – to investigate whether creditors' CDS exposure creates renegotiation frictions, and if so when these frictions are more pronounced. Using the amount of CDS contracts outstanding per dollar of total debt as a proxy for creditors' CDS exposure, we show that CDS related costs of inefficient renegotiations outweigh the benefits of deterring strategic default. Although CDS related renegotiation frictions are not economically significant, on average, we provide evidence that over-insurance in the CDS market creates economic costs. The results are robust to the inclusion of other strategic behavior proxies, implying that CDS create additional renegotiation frictions. We run several robustness tests to control for the bond liquidity, the simultaneity between credit spreads and CDS exposure, the measurement error in our CDS exposure proxy, the endogeneity issues, and the alternative dependent and independent variables, but the results do not change.

In addition, we report that the costs of CDS are more pronounced when liquidation costs are higher. This implies that firms with higher liquidation costs (lower expected recoveries in default) are likely to suffer more so from the increased probability of default since default is much costlier for these firms compared with out-of-court renegotiations. On the other hand, we also provide evidence that the benefits of CDS are more pronounced when debtor bargaining power is higher. When the debtors' interests are more in line with the shareholders', additional protection that CDS provide to the creditors reduces the probability that debtor may behave opportunistically.

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Appendix

Bloomberg Bond Search Output (Function: SRCH <GO>)

1. Select Universe — SRCH_Template

11) Asset Classes: Corporates — 1,272,892 securities

12) Sources: All Securities

2. Criteria / Ask a question

	Field	Boundaries	Selected Criteria	Matches
31)	Security Status	Include	Bonds: All	1,263,071
32) And	Ult Prnt Cntry Domicile	Include	(United States of America)	273,261
33) And	Country of Incorp	Include	(United States of America)	218,878
34) And	Currency	Include	(United States Dollar)	207,580
35) And	Sector/Industry Group	Exclude	(Banking or Commercial Finance or Consumer Finance or F	64,761
36) And	Maturity Type	Include	(Bullet) and not (Callable and Make Whole Call and Putabl	16,875
37) And	Coupon Type	Include	(Fixed or Zero Coupon)	14,469
38) And	Payment Rank	Include	(Sr Unsecured)	3,530
39) And	Issue Date	<=	12/31/2012	3,373
40) And	Maturity Date	>=	10/01/2008	2,250
41) And	Series	Exclude	(REGS, 144A)	2,169
42) And	Market Type	Exclude	(Private Placement)	1,977

Table 1 Credit Spread Sample

This table reports the credit spread (z-spread, daily) distributions by S&P long-term issuer credit ratings for a sample of Bloomberg and CRSP matched U.S. senior unsecured plain vanilla bond universe between October 2008 and December 2012. A bond is included in the sample if it has a maturity of 1- to 30-years as of the trade date, and its issuer is an investment grade non-financial firm with CDS contract outstanding that has stock price available at least within 1-year preceding the trade date. *Time-to-Maturity* is in years. Panel A reports the average credit spreads by each credit rating class. Panel B reports the credit spreads averaged at firm and credit rating level.

Rating	N	Mean	25%	50%	75%	St. Dev.	Time-to-Maturity
Panel A: Averaged over ratings							
AAA	9474	84.74	37.39	69.61	109.41	69.39	13.35
AA	33111	97.41	42.24	84.22	139.83	68.01	10.00
A	87840	172.34	77.57	141.72	239.14	124.90	8.52
BBB	64229	304.76	172.78	257.80	348.80	253.28	10.32
All	194654	199.03	83.49	157.43	266.81	188.76	9.60
Panel B: Averaged over firms and ratings							
AAA	5	160.50	118.06	120.07	164.34	111.62	11.43
AA	13	126.72	90.15	123.70	155.15	53.10	9.89
A	49	243.41	165.76	204.40	265.29	159.21	8.63
BBB	73	388.33	271.10	341.36	396.40	252.54	9.57
All	140	305.18	184.81	265.83	360.37	226.05	9.34

Table 2 Variables

This table reports firm characteristics for the sample firms described in Table 1. *Total debt* is the sum of short- and long-term debt. *Leverage* is the ratio of total debt to the market value of assets on the trade date. *Asset volatility* is the estimated volatility of a firm inferred from the market value of equity and iteratively solving the structural model of Merton (1974) (see Bharath and Shumway, 2008). *Bond trading volume* is the sum of the intraday bond volume in each week. *Time-to-maturity* is the bonds' time-to-maturity in years. *Non-fixed assets* is equal to (1 – Fixed assets/Assets). *Risk-free rate* is the rate on a 5-year Treasury bond. *Intangibility* is equal to {1 - (Cash and Equivalents + 0.715 x Receivables + 0.547 x Inventories + 0.535 x PP&E)/Assets}. *CEO shareholding* and *Managerial shareholding* are calculated as the number of shares held by the CEO and the aggregate number of shares held by the five highest paid managers divided by the total number of shares outstanding, respectively. *Net notional* is firm level CDS net notional from the Top 1,000 actively traded reference entity list of DTCC. When not available, we assume that net notional equals zero (Represents around 12% of the credit spreads). *Net notional dummy* is a dummy variable equals to 1 if the firm has net notional data, 0 otherwise. *Net notional/total debt* is the ratio of net notional to total debt. *Net notional/sen. unsec. debt* is equal to net notional divided by the total amount of senior unsecured debt. *Fama & French industry distribution* is based on the five-industry classification.

Variables	**N**	**Mean**	**Median**	**St. Dev.**
Distress variables and firm characteristics				
Assets ($ Billion)	123	45.54	23.13	82.39
Market value of equity ($ Billion)	123	38.85	18.94	57.07
Total debt ($ Billion)	123	13.41	5.81	44.96
Leverage (%)	123	27.88	24.14	16.32
Asset volatility (%)	123	30.18	30.26	9.73
Bond trading volume (Million)	123	3.54	1.71	6.75
Time-to-maturity (Years)	123	9.31	9.38	5.24
Risk-free rate (%)	123	1.74	1.66	0.28
Liquidation cost				
Non-fixed assets (%)	123	61.97	67.22	24.54
Intangibility (%)	123	58.49	56.88	10.94
Debtor bargaining power				
CEO shareholding (%)	122	0.53	0.23	1.13
Managerial shareholding (%)	122	0.88	0.53	1.23
CDS exposure				
Net notional dummy (%)	123	80.37	100.00	39.09
Net notional ($ Billion)	123	1.00	0.87	0.90
Net notional/Total debt (%)	123	20.14	9.54	25.27
Net notional/Sen. unsec. debt (%)	123	26.18	14.89	33.65
Fama & French industry distribution				
FF1 - Consumer (%)	123	22.99	0.00	42.05
FF2 - Manufacturing (%)	123	50.18	71.77	49.73
FF3 - High-tech (%)	123	9.96	0.00	29.81
FF4 - Health (%)	123	6.50	0.00	24.76
FF5 - Other (%)	123	10.37	0.00	30.35

Table 3 Correlation Matrix

This table reports the correlation coefficients between the variables of interest reported in Table 2. See Table 2 for the variable definitions.

	Net not./ tot. debt	Log (m.v. equity)	Leverage	Asset vol.	TTM	Log (1+bond vol.)	R_f	Non-fixed assets	Intangibility	CEO share	MNGR share
Net not./tot. debt	1.00										
log(m.v. equity)	-0.48	1.00									
Leverage	0.00	-0.48	1.00								
Asset volatility	0.24	-0.23	-0.03	1.00							
Time-to-maturity	0.04	0.00	-0.09	0.04	1.00						
log(1+bond volume)	-0.10	0.27	0.04	-0.04	-0.11	1.00					
Risk-free rate	0.09	-0.10	0.06	0.35	0.01	0.06	1.00				
Non-fixed assets	0.08	0.04	0.01	-0.11	-0.05	0.16	-0.04	1.00			
Intangibility	-0.12	0.04	0.22	-0.19	-0.07	0.05	0.00	0.45	1.00		
CEO share	0.04	-0.12	0.05	0.05	0.05	0.04	0.01	0.02	-0.05	1.00	
MNGR share	0.18	-0.26	0.11	0.11	0.08	-0.02	0.05	0.03	-0.06	0.94	1.00

Table 4 Credit Spread Distributions for the Regression Sample

This table reports credit spread (z-spread, weekly) distributions by S&P long-term issuer credit ratings for the regression samples. Table 1 provides the details of sample selection. The regression sample is a randomly selected subset of the sample where a firm contributes only one credit spread in each week. *Time-to-Maturity* is in years, *Has Net Notional* is a dummy variable equals to 1 if the firm has net notional data, 0 otherwise, and *Net Notional/Total Debt* is a proxy for CDS exposure. Panel A reports the average credit spreads by credit rating class. Panel B reports the same statistics for credit spreads averaged at firm level and rating level.

		Spread			**Time-to-Maturity**			**Net Notional Dummy**			**Net Notional/Total Debt**		
Rating	**N**	**Mean**	**Median**	**St. Dev.**	**Mean**	**Median**	**St. Dev.**	**Mean**	**Median**	**St. Dev.**	**Mean**	**Median**	**St. Dev.**
Panel A: Averaged over ratings													
AAA	674	111.67	96.70	78.36	13.57	11.40	7.55	0.69	1.00	0.46	4.18	5.16	3.34
AA	1979	125.50	121.05	84.15	9.44	7.93	6.61	0.85	1.00	0.36	6.41	5.58	4.84
A	6037	187.62	169.08	121.39	9.35	8.79	6.38	0.94	1.00	0.25	12.20	7.73	11.90
BBB	8084	332.35	292.52	220.94	10.25	10.43	6.45	0.87	1.00	0.34	28.19	17.03	32.09
All	16774	246.99	214.23	192.78	9.96	9.45	6.55	0.88	1.00	0.32	18.90	10.58	25.21
Panel B: Averaged over firms and ratings													
AAA	5	160.59	126.62	113.27	11.42	10.67	4.85	0.60	1.00	0.55	3.76	4.42	3.61
AA	13	129.39	124.67	54.22	9.84	9.47	4.71	0.85	1.00	0.38	5.61	5.22	3.65
A	49	240.75	199.30	166.73	8.68	9.26	4.69	0.87	1.00	0.32	14.40	9.10	15.09
BBB	73	381.04	331.73	245.54	9.56	9.38	5.45	0.77	1.00	0.42	27.31	17.24	29.66
All	140	300.70	264.97	222.62	9.34	9.43	5.09	0.81	1.00	0.39	19.94	10.29	24.57

Table 5 Credit Spread Regressions – Base Model

This table reports the average coefficient estimates from 218 weekly cross-sectional regressions, as in Fama and Macbeth (1973). See Table 4 for a definition of the regression sample. *Risk-free rate* is the interest rate on five-year Treasury bonds. *Leverage* is the ratio of total debt to the market value of the assets on the trade date. *Asset volatility* is the estimated volatility of a firm inferred from the market value of equity and iteratively solving the structural model of Merton (1974) (see Bharath and Shumway, 2008). *Log(m.v. equity)* is the natural logarithm of the market value of equity. *Time-to-maturity* is bond level time-to-maturity in years calculated on trade date. *Log(1+bond volume)* is the natural logarithm of bond trading volume. *Net notional dummy* is equal to 1 if net notional data is available, 0 otherwise. *Net notional/total debt* is the ratio of net notional to total debt. *Rating dummies* are based on S&P long-term issuer credit ratings (AAA, AA, etc.) and *Industry dummies* are based on the Fama&French five-industry classifications. Reported in parenthesis are *t-values* calculated using Newey-West adjusted standard errors.

	Credit Risk Model	**The Net Effect**	
Variables	**I**	**II**	**III**
Intercept	448.73***	389.26***	400.96***
	(8.66)	(7.47)	(7.47)
Risk-free rate	-58.73*	-53.37*	-52.16*
	(-1.97)	(-1.85)	(-1.82)
Leverage	1.84***	2.07***	2.03***
	(6.73)	(7.97)	(8.27)
Asset volatility	1.66***	1.57***	1.53***
	(10.87)	(10.00)	(10.74)
Log(m.v. equity)	-17.85***	-13.08***	-16.26***
	(-6.59)	(-4.27)	(-4.03)
Time-to-maturity	5.08***	5.11***	5.23***
	(11.39)	(11.49)	(12.65)
Log(1+bond volume)	-7.56***	-7.95***	-7.74***
	(-11.45)	(-11.35)	(-10.34)
Net notional/total debt		0.48***	0.37***
		(7.32)	(4.03)
Net notional dummy			21.10***
			(2.86)
Rating dummies	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes
$\overline{R}^2$	0.68	0.69	0.69
Number of obs.	16774	16774	16774

***,**,* indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 6 Robustness Regressions

This table reports the average coefficient estimates from weekly cross-sectional regressions, as in Fama and MacBeth (1973). See Table 4 for a definition of the regression sample. *Risk-free rate* is the interest rate on five-year Treasury bonds. *Leverage* is the ratio of total debt to the market value of the assets on the trade date. *Asset volatility* is the estimated volatility of a firm inferred from the market value of equity and iteratively solving the structural model of Merton (1974) (see Bharath and Shumway, 2008). *Log(m.v. equity)* is the natural logarithm of the market value of equity. *Time-to-maturity* is bond level time-to-maturity in years calculated on trade date. *Log(1+bond volume)* is the natural logarithm of bond trading volume. CDS exposure variable in Regression I is *Net notional/sen. unsec. debt* which is equal to net notional divided by the total amount of senior unsecured debt. CDS exposure variable in Regression II is 3-months lagged *net notional/total debt*. CDS exposure variable in Regression III is *net notional/total debt* and the sample only includes observations with available net notional. CDS exposure variable in Regression IV is *net notional/total debt*, but the dependent variable (credit spreads), time-to-maturity, and log(1+bond volume) are weekly weighted averages where weights are each bond's issue amount. *Rating dummies* are based on S&P long-term issuer credit ratings (AAA, AA, etc.) and *Industry dummies* are based on the Fama&French five-industry classifications. Reported in parenthesis are *t-values* calculated using Newey-West adjusted standard errors.

	Net. Not./ Sen. Unsec.	**Lagged Net. Not./Tot. Debt**	**W/O Missing Net Notional**	**W. A. Variables**
Variables	**I**	**II**	**III**	**IV**
Intercept	378.46***	340.94***	336.71***	324.68***
	(7.80)	(7.94)	(5.64)	(6.70)
Risk-free rate	-54.26*	-51.90*	-56.81*	-2.37
	(-1.88)	(-1.77)	(-1.81)	(-0.10)
Leverage	2.08***	1.81***	2.49***	2.12***
	(7.45)	(7.73)	(8.93)	(8.24)
Asset volatility	1.63***	1.47***	1.25***	1.54***
	(9.89)	(9.76)	(7.92)	(9.69)
Log(m.v. equity)	-12.66***	-9.62***	-8.73**	-12.53***
	(-4.80)	(-4.17)	(-2.02)	(-4.13)
Time-to-maturity	5.16***	5.61***	5.22***	5.02***
	(11.96)	(15.27)	(12.28)	(8.53)
Log(1+bond volume)	-7.89***	-8.59***	-8.25***	-8.33***
	(-11.56)	(-13.99)	(-9.99)	(-12.03)
CDS exposure	0.44***	0.50***	0.53***	0.53***
	(9.86)	(7.81)	(5.47)	(7.75)
Rating dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
$\bar{R}^2$	0.69	0.69	0.69	0.73
Number of obs.	16774	15760	14789	16774

***,**,* indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 7 Endogeneity Regressions

This table replicates the main results reported in Table 5 using an instrumental variable regression methodology. Reported are the average coefficient estimates from 218 weekly cross-sectional regressions, as in Fama and MacBeth (1973). See Table 4 for a definition of the regression sample. *First Stage* regression is a Tobit regression where the dependent variable is net notional/total debt. Tobit regression is censored below at the value of lowest net notional/total debt in each week. *Second Stage* regression is a cross-sectional OLS regression of credit spreads that uses predicted net notional/total debt from the weekly cross sectional first stage regressions. *Alternative IV – 1* column reports the results using *Log(1+CDX index notional)* as an IV. *Alternative IV – 2* column reports the results using *FX/Assets* (lenders/bond underwriters' average foreign exchange hedging positions divided by their total assets) as an IV. See Tables 2 and 5 for variable definitions and the methodology, respectively. *Rating* and *Industry dummies* are included, but not reported for brevity. Reported in parenthesis are *t-values* calculated using Newey-West adjusted standard errors.

	Alternative IV - 1		**Alternative IV - 2**	
	First Stage	**Second Stage**	**First Stage**	**Second Stage**
Variables	**I**	**II**	**III**	**IV**
Intercept	159.70***	358.09***	126.40***	354.51***
	(16.39)	(7.20)	(12.67)	(4.32)
Risk-free rate	-1.71	-44.04	-0.36	-50.46*
	(-0.29)	(-1.52)	(-0.06)	(-1.70)
Leverage	-0.85***	1.98***	-0.61***	2.24***
	(-79.58)	(6.84)	(-47.35)	(10.99)
Asset volatility	0.01	1.65***	0.24***	1.33***
	(-2.28)	(10.76)	(13.64)	(7.36)
Log(m.v. equity)	-14.35***	-14.25***	-11.77***	-12.58**
	(-49.4)	(-5.81)	(-41.96)	(-2.03)
Time-to-maturity	-0.05**	5.11***	0.01	5.29***
	(-2.28)	(11.52)	(0.53)	(12.70)
Log(1+bond volume)	0.35***	-7.72***	0.26***	-8.20***
	(5.76)	(-11.63)	(3.51)	(-11.30)
Log(1+CDX index notional)	0.85***			
	(49.21)			
FX/Assets			2.32***	
			(18.15)	
Predicted net notional/total debt		0.31***		1.11***
		(3.60)		(4.22)
Rating dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
$\overline{R}^2$	.	0.68	.	0.68
Number of obs.	16774	16774	16774	16774

***,**,* indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 8 Credit Spread Regressions – Interaction Model

This table reports the average coefficient estimates from 218 weekly cross-sectional regressions, as in Fama and MacBeth (1973). See Table 4 for a definition of the regression sample. All of the regression models include *Credit risk variables, Rating dummies, and Industry dummies* as control variables, but do not reported them for brevity. *Net notional/total debt* is the ratio of net notional to total debt. *Intangibility* is equal to {1 - (Cash and equivalents + 0.715 x Receivables + 0.547 x Inventories + 0.535 x PP&E)/Assets}. *Non-fixed assets* is equal to (1 – Fixed assets/Assets). *CEO shareholding* and *Managerial shareholding* are calculated as the number of shares held by the CEO and the aggregate number of shares held by the five highest paid managers divided by the total number of shares outstanding, respectively. The *Interaction* term is the residual from the weekly cross-sectional regression of interaction variable (e.g. AxB) on the components of the interaction term ($\bar{\varepsilon}_{i,t} = A_{i,t} \, x \, B_{i,t} - \bar{\alpha}_t - \bar{\beta}_{A,t} A_{i,t} - \bar{\beta}_{B,t} B_{i,t}$). Reported in parenthesis are *t-values* calculated using Newey-West adjusted standard errors.

	Liquidation Costs		**Debtor Bargaining Power**	
Variables	**I**	**II**	**III**	**IV**
CDS exposure				
Net notional/total debt	0.49***	0.53***	0.49***	0.53***
	(6.89)	(13.13)	(6.97)	(7.75)
Liquidation costs				
Intangibility	0.20*			
	(1.93)			
Non-fixed assets		-0.04		
		(-1.20)		
Debtor bargaining power				
Managerial shareholding			0.09	
			(0.09)	
CEO shareholding				3.46*
				(1.86)
Interaction of CDS exposure	0.02***	0.01***	-0.25***	-0.14***
	(4.70)	(7.44)	(-2.78)	(-3.23)
Credit risk variables	Yes	Yes	Yes	Yes
Rating dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
$\bar{R}^2$	0.70	0.70	0.70	0.70
Number of obs.	16774	16774	16697	16695

***,**,* indicate significance at the 1%, 5%, and 10% levels, respectively.